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Shoot-at-will: the effect of mass-shootings on US small gun manufacturers

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Abstract

Mass shootings have become a frequent occurrence in the US, attracting extensive media coverage and provoking public condemnation. The financial impact of such tragedies are seldom examined. In this study, we use an event study methodology to analyse the impact of 83 mass shootings on the value of 15 US gun and ammunition manufacturers from 1982 to 2017. In contrast to previous findings, we find no statistically significant impact on the returns of these firms, suggesting investors no longer fear the threat of restrictive regulation that may negatively affect these businesses.

Keywords: Mass-shootings; sin stocks; event-study; cross-correlation.

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1 Introduction

Mass shootings have become an all too frequent occurrence (Cohen et al., 2014; Steeves and Costa, 2017), attracting extensive media coverage and provoking strong reactions

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from society. The recent Florida high school incident was notorious for the huge public outcry it gave rise to, followed by social and political movements calling for legislative reform to impose tighter controls and curb gun violence (Katsiyannis et al., forthcoming).

The companies that manufacture and sell guns may be affected by such events in different ways. On the one hand, they may suffer the negative association with such tragic events, seen as providing the instruments that enable such criminal acts, and thus gain condemnation and ill repute. Pacifist movements gain momentum, advocating for greater gun control and eliciting social pressure against gun ownership that may dissuade new gun buyers. This is more likely to impact the public at large, but financial investors are increasingly concerned with social and ethical matters (Svensson et al., 2010) and may also rethink their investment decisions and eschew gun manufacturers. It is possible to find media posts advising on how to divest from gun stocks (e.g., Adamczyk, 2018) in the wake of the 2018 Florida high school shooting. The price of so-called "sin" or "vice" stocks (stocks from companies in industries such as gambling, tobacco, alcohol and firearms) seems to be affected by investor sentiment (Liston, 2016). These companies also pay more in auditing and consulting services fees (Leventis et al., 2013). And there is reported evidence of negative impact on the stock prices of companies associated with school massacres, including the related gun manufacturer as well as their competitors (Cross and Pruitt, 2013) or the small arms industry as a whole (Steeves and Costa, 2017).

On the other hand, events that threaten people's sense of security, criminality and violence in society in general, may elicit fear of victimisation and prompt protective responses that include buying more guns (Kupchik and Bracy, 2009). Some people feel safer having their own guns as a way of protecting themselves. Indeed, the need for self-protection is reported as the main reason to own a gun (Wallace, 2015). Mass shooting events, especially those that draw extensive media coverage, seem to incite people to buy more guns rather than less (Cross and Pruitt, 2013; Gopal and Greenwood, 2017), thereby bolstering gun manufacturers' business. There is evidence that gun ownership increases when there is heightened fear of crime and/or deficient police protection. Guns in circulation have increased in the last 10 years in the USA, as has membership of the American organisation NRA (National Rifle Association) (Wallace, 2015).

Expressive public outrage may pressure governments into action regarding gun policy and law. They call for changes to the current regulations to produce stricter rules regarding gun ownership, including introducing or tightening background checks on prospective gun owners and restrictions to the kinds of weapons and ammunition that can be sold to the public (Katsiyannis et al., forthcoming). The ongoing debate about gun control in the United States is a case in point. Paradoxically, fear of stricter rules, that limit access to guns, may therefore also spur gun sales on the short-run, as people hasten gun purchases to avoid possible restrictions (Cross and Pruitt, 2013).

The severity of events may be a relevant factor on the magnitude of such effects. We consider the severity of mass shooting events based on the number of people killed, whether they involve children as victims or if there are any religious undertones, such as mass shootings that occur in churches. School related events in particular seem especially prone to eliciting legislative changes (Katsiyannis et al., forthcoming) in addition to shocking the general public and attracting singular media attention (Schildkraut et al., 2015). We expect that, if there is any effect, it should be stronger around those events, because the higher the severity of the event, the more likely it is to entice media, public and political reaction.

Media coverage greatly influences people's perceptions of violent events, especially when using emotional accounts of the events by victims or witnesses (Wallace, 2015). Media exposure thus generates moral panic (Schildkraut et al., 2015), amplifying people's sense of threat and the need for self-protection (Kupchik and Bracy, 2009). Media exposure may even have a stronger impact on acute stress that direct exposure to the events (Holman et al., 2014).

In this study we analyse the effects of mass shootings on the short-term returns of US gun and ammunition manufacturing companies around those events.

There are few studies that examine the impact of mass shootings on the stock market performance of related firms. Cross and Pruitt (2013) examined the impact of two mass shootings, one in a theatre and one in a school, on the price of theatres and of gun manufacturers. They found significant impact in the case of the value of the theatre where the tragedy took place, with risk-adjusted abnormal returns falling by over 4% on the day of the shootings and nearly 2% on the next day. A similar impact was found for three US competitor theatres, pointing to a contagion effect. However, no impact was felt in the stock price of the gun manufacturer of the weapon used in the attack, while this company's main US competitor's stock price actually rose. In the case of the school shooting, Cross and Pruitt (2013) found a significant negative impact on the returns of two major US gun manufacturers (neither directly related to the incident), with stock prices falling dramatically (as much as 10% and 14%), especially on the second and third days after the shooting.

Steeves and Costa (2017) analysed the impact of six mass shootings, occurring between 2007 and 2013, on the returns of two US and one Brazilian gun manufacturers. They found negative but not significant impact on each firms' returns. They did find evidence of significant impact on the collective small arms industry by using an equally weighted portfolio of the arms companies across all six events. In this case, the value of the portfolio fell significantly in the week following the attacks, and this was more pronounced in incidents with the greater number of victims.

Gopal and Greenwood (2017)'s study is the more complete to date, assessing the impact on the stock prices of two publicly traded US firearm manufacturers of 93 mass shootings in the US from 2009 to 2013. They find a significant decrease in the stock prices of these firms over a 2, 5, and 10 day window after the event. The immediate market reaction (up to 2 days) was stronger in incidents with a greater number of victims, but was unaffected by the presence of children as victims. Interestingly, they also found the negative effects to be greater in an earlier period, but then to lose significance in later incidents. The authors suggest this may indicate a greater expectation of regulation changes in the early years of the Obama administration, that later faded as previous occurrences resulted in no new laws.

These few earlier studies present some shortcomings in that they analyse few companies (e.g., Gopal and Greenwood, 2017; Steeves and Costa, 2017), few mass shooting incidents (e.g., Cross and Pruitt, 2013; Steeves and Costa, 2017), or short time spans (especially Cross and Pruitt, 2013). Specific methodological choices may explain the observed disparity in results, including focusing on isolated events versus focusing on several events collectively; the number of events and firms considered; and the methodology used by the authors. Gopal and Greenwood (2017), the only other study that considers a large number of mass shooting incidents, ignores the problem of cross-correlation, thereby overstating the tests statistics and increasing the likelihood of rejecting the null hypothesis even when it is true. We overcome most of these limitations by: considering a larger number of companies involved (15) in the manufacturing of small guns, producing ammunition or accessories for them; covering a 35-year period of mass shooting incidents; and using robust statistical methods that account for cross-correlation and event-induced volatility.

2 Methodology

To study the short term impact of mass shooting incidents on the returns of small arms and ammunition manufacturers we use the classic event study methodology. This methodology is widely used, and ”relatively straight forward and trouble free” (Kothari and Warner, 2007).

When events are clustered, as is the case of the present study, there will be as a resulting cross-sectional correlation between firm returns. Kolari and Pynnonen (2010) show that cross-correlation, even when relatively low, can lead to over-rejection of the null hypothesis of zero average (cumulative) abnormal returns even when the hypothesis is true. This is caused by underestimating the standard deviation of the abnormal returns, as the cross-correlation is assumed to be zero and it can actually be positive in these cases, consequently inflating the rejection rate of the test statistic.

This problem is often addressed by using an equally weighted portfolio of returns as has been suggested by Jaffe (1974). Although the portfolio approach can solve the problem of cross-correlation between firm returns, it is not an optimal solution as the method lacks power and can also be misspecified in the presence of event induced volatility (Kolari and Pynnonen, 2010).

We will therefore use the Boehmer et al. (1991) adjusted test suggested by Kolari and Pynnonen (2010), that is able to account for the presence of both cross-sectional correlation and event-induced volatility. Kolari and Pynnonen (2010) have shown that this test is robust to these problems but also to have more power than the portfolio method.

We estimate expected returns using a 250 day window [-252, -3], using different models. To reduce the cross-correlation to a minimum, we use various multi-factor models that will capture as much as possible the cross-correlation from the model residuals: the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model and the Fama and French (2015) five-factor model.

The Appendix provides details on the event study methodology we follow.

3 Data

Systematic data about mass shootings are hard to obtain because of variation in definitions. Related research studies are further hindered by laws that block funding to be used in studies that may promote firearm control (Katsiyannis et al., forthcoming). Although there is no standard definition of what constitutes a "mass shooting" in the US, the FBI define "mass murder as the killing of four or more people in the same incident" (Katsiyannis et al., forthcoming, p.3).

In this study we use data from Mother Jones (Follman et al., 2018), who follow the FBI reference of incidents where four or more people are killed for data up to 2012, and lower the minimum number of victims to three for incidents after 2013, following the guidelines in President Barack Obama's mandate for a federal investigation of mass shootings. This database excludes "shootings stemming from more conventional crimes such as armed robbery or gang violence" (Follman et al., 2018). As our financial data extends up to 31 December 2017, we consider only incidents occurring before that date.

We start by considering 95 mass shooting incidents in the USA, from August 1982 to December 2017, as depicted in Figure 1. This figure presents the mass shooting incidents over time, as well as the number of fatalities and type of venue where these shootings took place. Of these, 28 happened in workplaces, 15 were school shootings, five took place in places of worship, five in military facilities. In three of these incidents, more than 30 people were killed; seven caused more than 20 dead, and 16 counted 10 or more fatal victims. In only 15 of these episodes did the perpetrator use illegally obtained weapons. As can be observed, these incidents occur quite frequently, and twelve of them occur within a window of eleven days of a previous incident. To avoid overlapping events, we ignore any incident that occurs inside the event window of a previous incident. We therefore analyse a total of 83 mass shooting events.

[Figure 1 about here.]

We identified companies that belong to one of the following standard industrial classification (sic) code: 3480 - Ordnance & Accessories, (no Vehicles/guided Missiles); 3482 - Small Arms Ammunition; 3484 - Small Arms; 3489 - Ordnance and Accessories, Not Elsewhere Classified.

Daily firm data, including returns and industry classification, were collected from the Center for Research in Security Prices (CRSP) database, for the period from 1st January 1981 to 31st December 2017. Our data set contains 15 companies belonging to one of those industry classification codes, over the referred period. The number of events per company ranges from 83 (two firms) to 1 event (two firms) with an average of about 28 events per company over the analysed period.

The daily factor data, market returns and risk-free rates required to estimate expected returns were collected from Professor Kenneth French's website.[4]

4 Results

We start by analysing the results for all shooting incidents over the period. We then proceed to analyse sub-samples of those incidents as we posit that events with a larger number of fatalities, or that take place in religious venues and schools, are more likely to entice media, public and political reaction, and consequently could negatively affect company values.

4.1 All events

We present results for expected returns estimated using the Carhart (1997) four-factor model. We also performed the same tests using the expected returns from the Fama and French (1993) three-factor model, and Fama and French (2015) five-factor model. The results of the tests using these three different models are materially the same and available from the authors upon request.

Table 1 shows the results for average abnormal returns (AAR) and their respective statistical tests. There are no statistically significant abnormal negative returns.

[Table 1 about here.]

Figure 2 depicts the results for the average cumulative abnormal returns (ACAR) for each day in the event windows [-2,+10] and [0,+10]. Time 0 in the event window

[4]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

correspond to the day of the shooting incident if that day corresponds to a trading day, or otherwise the next trading day.

[Figure 2 about here.]

The [-2,+10] window shows no sign that the events are anticipated by the market, which is to be expected due to the complete random nature of the incidents. Table 1 present the results for the ACAR for different event windows: [-2,+10], [0,+10], [+2,+10], [+5,+10], [0,+5], [+2,+5]. There is no evidence of statistically significant negative ACARs for any of the windows.

[Table 2 about here.]

4.2 Incidents with more than 10 fatalities

To take into account the severity of mass shooting events, we separately examine incidents with more than 10 fatalities (16 events), more than 20 (7 events) and more than 30 (3 events) during the analysed period. Tables 3 and 4 show the results for the AAR and ACAR for severe incidents with more than 10 deceased. The results are surprising as none of the event windows ACARs are statistically significant. Results for incidents with more than 20 and more than 30 fatalities were, again, all non-significant.

[Table 3 about here.]

[Table 4 about here.]

4.3 Incidents in places of worship and schools

Other aspects of severity considered were the presence of children as the main targets and a religious connection. There are 5 incidents in places of worship and 15 incidents of mass shootings in schools in our sample. Tables 5 and 6 present the results for each sample. Again, there are no statistically significant AARs and ACARs for either incidents that take place in schools or in places of worship. Therefore we can conclude that investors do not consider these incidents to carry any different consequences than other mass shooting events.

[Table 5 about here.]

[Table 6 about here.]

5 Conclusions

We analyse the impact on the market value of US small arms and ammunition manufacturers in the wake of mass shootings. We consider the period 1982 to 2017, covering 35 years of these tragic incidents and associated financial data. Eighty three events and 15 listed US gun and ammunition manufacturers are included in the study. We use an event study methodology and test average abnormal returns and cumulative average abnormal returns using the method proposed by Kolari and Pynnonen (2010) that is able to deal with both cross-correlation due to event clustering and also the increased volatility induced by the event.

Our results show that, although mass shootings give rise to negative average cumulative abnormal returns, they are never statistically significant. This holds for the complete set of analysed events, for all companies, during the entire period considered. It holds also when taking into account the severity of the events, either considering the number of victims and the presence of children or religious communities.

This is in stark contrast with the findings of previous studies that typically encountered significant negative impact on firms' returns, at least in some of the days following the tragic events and when considering the incidents collectively. The lack of effect for more severe incidents also diverges from previous findings, where the number of fatalities was associated with greater negative impact (Gopal and Greenwood, 2017; Steeves and Costa, 2017). The fact that the presence of children has no effect is in line with the findings of Gopal and Greenwood (2017). This illustrates that tests that ignore the problem of cross-correlation can in fact produce type I errors, giving the impression that results are statistically significant when in fact they are not.

Our results show that vigorous demonstrations of public outcry and extensive media attention such distressing incidents invariably garner elicit no such reaction from the stock market. These results indicate that investors do not expect mass shootings to substantially change the value of these companies.

Explanations for this can be that mass shootings have become so frequent as to be considered "the new normal" (Graham, 2018) and are expected by investors in gun manufacturers, eliciting no great reaction from them.

What may be less predictable is the level of public and political repercussions, in particular whether these events will bring about legislative and regulatory changes that restrict access to guns. What seems to be happening is that successive tragedies that generate fierce public indignation but elicit no changes in gun control laws have made investors expect no negative impact on the business of firearm manufacturers. The media attention and public outrage usually subsides. Recent history shows that none of these events resulted in substancial changes in gun regulation that impact these firms' activities. Also, the increased sales of guns that sometimes follows such events (Cross and Pruitt, 2013; Gopal and Greenwood, 2017; Kupchik and Bracy, 2009) can counteract the negative reputation that these firms might experience.

Appendix - event study methodology

To calculate the abnormal returns (AR) we first estimate, for each event and firm, the Carhart (1997) four-factor model using 250 daily returns in the window of [-252, -3]. As a robustness check, we also estimate AR with the Fama and French (1993) three-factor model and the Fama and French (2015) five-factor model.

The Fama and French (1993) three-factor model is estimated using the following regression:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{M,i}(r_{M,t} - r_{f,t}) + \beta_{SMB,i}(SMB_t) + \beta_{HML,i}(HML_t) + \epsilon_{i,t} \quad (1)$$

for each firm i, and day t, $r_{i,t}$ is the firm return; $r_{M,t}$ is the market return proxied by the value weighted CRSP market index; $r_{f,t}$ is the return of the risk-free asset; SMB_t, HML_t are the returns on a small minus big and high minus low portfolios, respectively; and $\epsilon_{i,t}$ is a zero-mean residual. The coefficients $\beta_{SMB,i}$, $\beta_{HML,i}$ will capture the size and value effects.

The Carhart (1997) four-factor model adds momentum to the three-factor model:

$$\begin{aligned} r_{i,t} - r_{f,t} = &\alpha_i + \beta_{M,i}(r_{M,t} - r_{f,t}) + \beta_{SMB,i}(SMB_t) + \beta_{HML,i}(HML_t) + \\ &\beta_{MOM,i}(MOM_t) + \epsilon_{i,t} \end{aligned} \quad (2)$$

where MOM_t is the return of the momentum portfolio.

The five-factor model of Fama and French (2015) is estimated using the following expression:

$$\begin{aligned} r_{i,t} - r_{f,t} = &\alpha_i + \beta_{M,i}(r_{M,t} - r_{f,t}) + \beta_{SMB,i}(SMB_t) + \beta_{HML,i}(HML_t) + \\ &\beta_{RMW,i}(RMW_t) + \beta_{CMT,i}(CMT_t) + \epsilon_{i,t} \end{aligned} \quad (3)$$

where RMW_t is the profitability factor, given by the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and CMA_t is the investment factor given by the difference between the returns on diversified portfolios of the stocks of low and high investment firms. [5]

The daily abnormal returns (AR) for the event window [-2, +10] for each firm are then computed in the usual way, subtracting the expected excess return from the firm excess realised return. For the three-factor model the AR is computed as:

[5] Please note that the size factor (SMB) in three-factor model is computed as the average return on the three small portfolios minus the average return on the three big portfolios, whilst in the five-factor model it is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios. For more details on these multi-factor models, please refer to Carhart (1997) and Fama and French (1993, 2015)

$$AR_{i,t} = r_{i,t} - r_{f,t} - (\alpha_i + \beta_{M,i}(r_{M,t} - r_{f,t}) + \beta_{SMB,i}(SMB_t) + \beta_{HML,i}(HML_t)) \quad (4)$$

for the four-factor model as:

$$\begin{aligned} AR = & r_{i,t} - r_{f,t} - (\alpha_i + \beta_{M,i}(r_{M,t} - r_{f,t}) + \beta_{SMB,i}(SMB_t) + \\ & \beta_{HML,i}(HML_t) + \beta_{MOM,i}(MOM_t)) \end{aligned} \quad (5)$$

and finally for the five-factor model as:

$$\begin{aligned} AR = & r_{i,t} - r_{f,t} - (\alpha_i + \beta_{M,i}(r_{M,t} - r_{f,t}) + \beta_{SMB,i}(SMB_t) + \\ & \beta_{HML,i}(HML_t) + \beta_{RMW,i}(RMW_t) + \beta_{CMT,i}(CMT_t)) \end{aligned} \quad (6)$$

The cumulative abnormal returns (CAR) for the period $[t_1, t_2]$ is computed by summing the abnormal returns over the event period t_1 to t_2:

$$CAR_i[t_1, t_2] = \sum_{t=t_1}^{t_2} AR_{i,t} \quad (7)$$

As recommended by Patell (1976) and Kolari and Pynnonen (2010), among others, we use scaled abnormal returns (SAR) to perform the statistical tests:

$$SAR_{i,t} = \frac{AR_{i,t}}{s_i\sqrt{1 + d_t}} \quad (8)$$

where s_i is the regression residual (ϵ) standard deviation and $d_t = x_t'(X'X)^{-1}x_t$, with vector x_t of all explanatory variable values, including the constant, and matrix X containing the explanatory variable values in the estimation period. This adjustment accounts for the increase in variance from prediction of abnormal returns done outside the estimation window and will give more weight to less noise estimates. Scaled abnormal returns will be used in the statistical tests but, since they are not easily interpreted, abnormal returns are the ones reported.

The cumulative scaled abnormal returns (CSAR) for the period $[t_1, t_2]$ is computed by summing the scaled abnormal returns over the event period t_1 to t_2:

$$CSAR_i[t_1, t_2] = \sum_{t=t_1}^{t_2} SAR_{i,t} \tag{9}$$

The average abnormal returns (AAR), average scaled abnormal returns (ASAR), average cumulative abnormal returns (ACAR) and average cumulative scaled abnormal returns (ACSAR) are given by:

$$AAR = \frac{1}{N} \sum_{i=1}^{N} AR_{i,t} \tag{10}$$

$$ASAR = \frac{1}{N} \sum_{i=1}^{N} SAR_{i,t} \tag{11}$$

$$ACAR = \frac{1}{N} \sum_{i=1}^{N} CAR_{i,t} \tag{12}$$

$$ACSAR = \frac{1}{N} \sum_{i=1}^{N} CSAR_{i,t} \tag{13}$$

with N as total number of events.

The Boehmer et al. (1991) test statistic is given by:

$$t_{BMP} = \sqrt{N} \frac{ASAR}{s} \tag{14}$$

where s is the cross-sectional standard deviation of the event-day scaled abnormal returns:

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(SAR_{i,t} - ASAR_t)} \tag{15}$$

Kolari and Pynnonen (2010) propose a modification of the Boehmer et al. (1991) test statistic to deal with both cross-correlation due to event clustering and also the increased volatility induced by the event:

$$t_{KP} = t_{BMP}\sqrt{\frac{1-\bar{r}}{1+(N-1)\bar{r}}} \tag{16}$$

with $\bar{r}$ as the mean of the sample cross-correlation of the estimation period residuals.

For testing the significance of ACSAR we can use the Boehmer et al. (1991) test statistic as given by:

$$t^*_{BMP} = \sqrt{N}\frac{ACSAR}{s^*} \tag{17}$$

where $s*$ is the cross-sectional standard deviation of the event-day cumulative scaled abnormal returns:

$$s^* = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(CSAR_{i,t} - ACSAR_t)} \tag{18}$$

The previous test can be adapted, as suggested by Kolari and Pynnonen (2010), to deal with both cross-correlation and event induced volatility. The adjustment remains the same as before, and the test statistic is the following:

$$t^*_{KP} = t^*_{BMP}\sqrt{\frac{1-\bar{r}}{1+(N-1)\bar{r}}} \tag{19}$$

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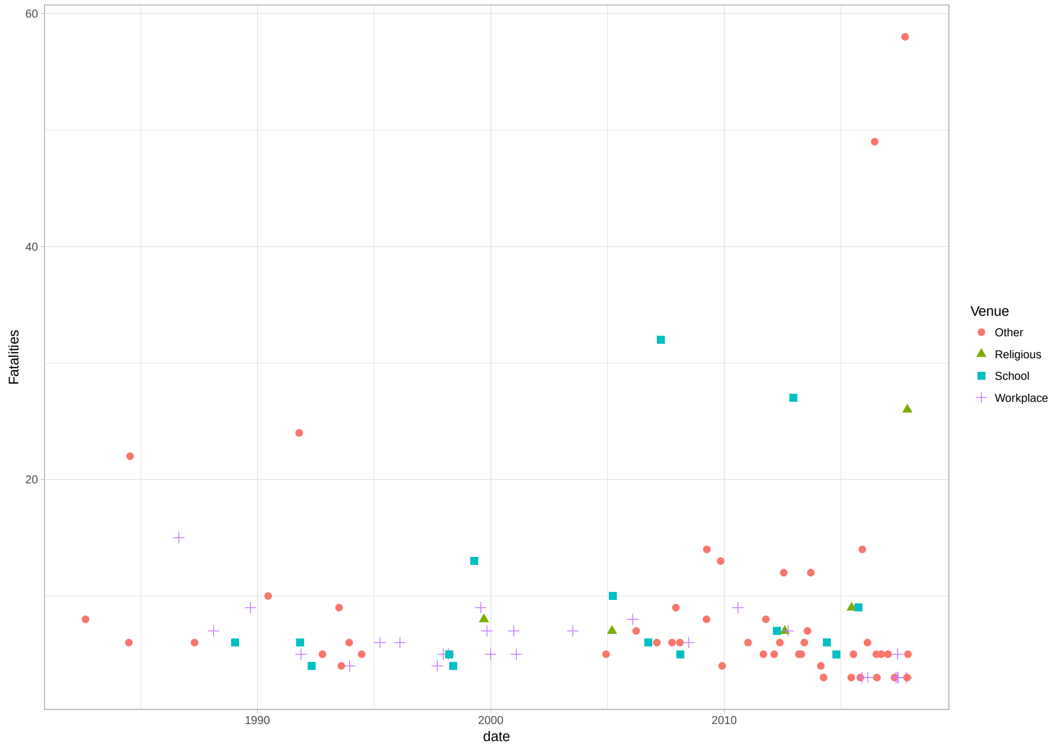
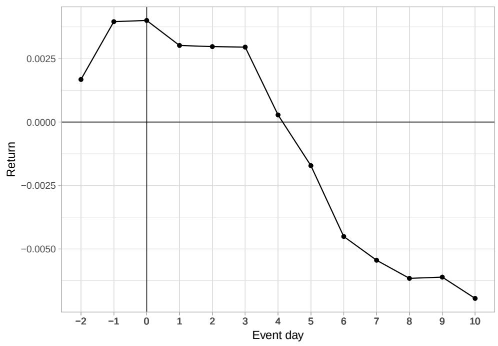
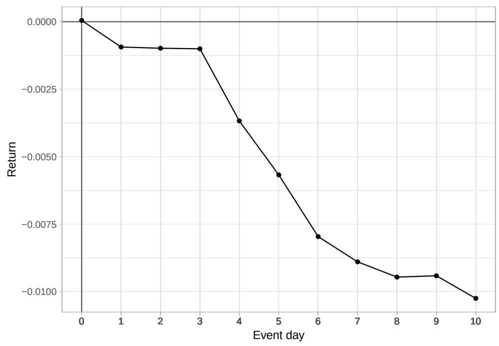


Figure 1 – Mass shootings incidents over time, from August 1982 to December 2017. Source: Mother Jones.



(a) [-2,+10]



(b) [0,+10]

Figure 2 – Average cumulative abnormal returns (ACAR) over the event window of [-2,+10] (a) and [0,+10] (b). Expected returns are estimated using the Carhart (1997) four-factor model. Please refer to the Appendix for details on the estimation of abnormal returns, and the ACAR.

Table 1 – Average abnormal returns for all shooting incidents from August 1982 to December 2017

Event day	AAR	KP p-value
-2	0.0016775	0.796
-1	0.0022781	0.739
0	0.0000477	0.770
1	-0.0009852	0.884
2	-0.0000453	0.968
3	-0.0000199	0.924
4	-0.0026727	0.670
5	-0.0019986	0.787
6	-0.0023971	0.784
7	-0.0004108	0.849
8	-0.0001308	0.999
9	0.0000780	0.994
10	-0.0008381	0.936

Average abnormal returns (AAR) over the event window of [-2,+10]. Expected returns are estimated using the Carhart (1997) four-factor model. The reported p-value uses the scaled abnormal returns and the Kolari and Pynnonen (2010) test that is robust to cross-correlation and event induced correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Please refer to the Appendix for details on the estimation of abnormal returns, ACAR and the test.

Table 2 – Average cumulative abnormal returns for all shooting incidents from August 1982 to December 2017

Event window	ACAR	KP p-value
$[-2, 10]$	-0.0069481	0.816
$[0, +10]$	-0.0102519	0.702
$[+2, +10]$	-0.0087516	0.659
$[+5, +10]$	-0.0061562	0.705
$[0, +5]$	-0.0056740	0.847
$[+2, +5]$	-0.0047365	0.757

Average cumulative abnormal returns (ACAR) over different event windows. Expected returns are estimated using the Carhart (1997) four-factor model. The reported p-value uses the scaled abnormal returns and the Kolari and Pynnonen (2010) test that is robust to cross-correlation and event induced correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Please refer to the Appendix for details on the estimation of abnormal returns, ACAR and the test.

Table 3 – Average abnormal returns for shooting incidents with more than 10 fatalities, from August 1982 to December 2017

Event day	AAR	KP p-value
-2	-0.0002475	0.758
-1	0.0024913	0.709
0	0.0010967	0.445
1	-0.0037946	0.812
2	-0.0016885	0.987
3	-0.0000304	0.986
4	0.0064786	0.331
5	-0.0039994	0.587
6	-0.0019820	0.808
7	-0.0028159	0.652
8	0.0024819	0.655
9	-0.0003175	0.818
10	0.0009028	0.901

Average abnormal returns (AAR) over the event window of [-2,+10]. Expected returns are estimated using the Carhart (1997) four-factor model. The reported p-value uses the scaled abnormal returns and the Kolari and Pynnonen (2010) test that is robust to cross-correlation and event induced correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Please refer to the Appendix for details on the estimation of abnormal returns, ACAR and the test.

Table 4 – Average cumulative abnormal returns for shooting incidents with more than 10 fatalities, from August 1982 to December 2017

Event window	ACAR	KP p-value
$[-2, +10]$	-0.0014244	0.542
$[0, +10]$	-0.0036682	0.645
$[+2, +10]$	-0.0009703	0.767
$[+5, +10]$	-0.0057301	0.977
$[0, +5]$	-0.0019375	0.689
$[+2, +5]$	0.0007604	0.843

Average cumulative abnormal returns (ACAR) over different event windows. Expected returns are estimated using the Carhart (1997) four-factor model. The reported p-value uses the scaled abnormal returns and the Kolari and Pynnonen (2010) test that is robust to cross-correlation and event induced correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Please refer to Appendix for details on the estimation of abnormal returns, and ACAR and the test.

Table 5 – Average abnormal returns for shooting incidents that took place in a school or religious venue, from August 1982 to December 2017

	Schools		Places of worship	
Event day	AAR	KP p-value	AAR	KP p-value
-2	0.0059097	0.441	-0.0057985	0.879
-1	-0.0006771	0.749	0.0078234	0.318
0	-0.0037543	0.700	-0.0020495	0.363
1	-0.0021226	0.552	0.0040733	0.247
2	-0.0021025	0.755	0.0015115	0.797
3	-0.0005257	0.851	-0.0251835	0.164
4	-0.0034045	0.244	-0.0009981	0.874
5	-0.0020554	0.508	0.0004809	0.983
6	0.0017415	0.650	-0.0025160	0.815
7	-0.0017369	0.560	-0.0044891	0.744
8	-0.0044952	0.240	0.0057466	0.393
9	-0.0003663	0.902	-0.0003360	0.940
10	0.0002670	0.959	-0.0076701	0.303

Average abnormal returns (AAR) over the event window of [-2,+10]. Expected returns are estimated using the Carhart (1997) four-factor model. The reported p-value uses the scaled abnormal returns and the Kolari and Pynnonen (2010) test that is robust to cross-correlation and event induced correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Please refer to the Appendix for details on the estimation of abnormal returns, ACAR and the test.

Table 6 – Average cumulative abnormal returns for shooting incidents that took place in a school or religious venue, from August 1982 to December 2017

	Schools		Places of worship		
Event window	ACAR	KP p-value	ACAR	KP p-value	
$[-2, +10]$	-0.0176087	0.658		-0.0294050	0.647
$[0, +10]$	-0.0211668	0.501		-0.0314300	0.476
$[+2, +10]$	-0.0185257	0.446		-0.0334538	0.386
$[+5, +10]$	-0.0124822	0.463		-0.0087837	0.942
$[0, +5]$	-0.0127077	0.544		-0.0221653	0.284
$[+2, +5]$	-0.0100665	0.480		-0.0241892	0.193

Average cumulative abnormal returns (ACAR) over different event windows. Expected returns are estimated using the Carhart (1997) four-factor model. The reported p-value uses the scaled abnormal returns and the Kolari and Pynnonen (2010) test that is robust to cross-correlation and event induced correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Please refer to the Appendix for details on the estimation of abnormal returns, ACAR and the test.

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